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Abstract:
We developed several nonparametric modeling techniques as well as nonlinear controller design techniques. We successfully implementing these techniques on a robot arm. We used a locally weighted modeling approach as the basis of our nonparametric modeling technique. Locally weighted modeling avoids negative interference by retaining the original training data, so the approach is adaptive to changing data distributions. We used sophisticated representations of high dimensional sub-manifolds to enable dynamic programming in higher dimensional spaces than are currently possible.

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Final Report: Nonparametric Modeling and Control of High Performance Maneuvers

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1 Objectives

There were two major objectives in this project: to develop a practical nonparametric modeling approach and a complementary nonlinear control design approach for high performance maneuvers. The desired characteristics of the nonparametric modeling approach were:

- The approach can be applied automatically or with minimal human supervision.
- The approach can be applied for online system identification.
- The approach does not suffer from interference.
- The approach reduces the cost of nonlinear modeling.

The desired characteristics of the nonlinear control design approach were:

- The approach can be applied automatically or with minimal human supervision.
- The controller designs can be based on the identified nonparametric models.
- The approach reduces the cost of nonlinear controller design.

The approaches developed were to be explored theoretically, in simulation, and in an actual implementation.

2 State Of The Art

Research on nonlinear modeling techniques advances the state of the art in nonlinear and learning control. A major challenge in the control of complex vehicles is dealing with the nonlinear dynamics of the vehicle. Learning algorithms are beginning to be applied for nonlinear control, with the most promising applications coming in situations classically handled with gain scheduling or with nonlinear inversion. These "classical" approaches exploit detailed mathematical models of the nonlinear dynamics; the promise of learning algorithms is that high fidelity nonlinear control might be implemented even when suitable first principle nonlinear models of the dynamics are lacking or expensive to obtain.

Using a nonlinear parametric model typically requires an assumption that the model structure is correct. This is rarely the case, and motivates the search for modeling techniques

that can correct structural modeling errors. In cases where nonlinear models based on fixed structure neural networks have been shown to be able to approximate any function, large amounts of resources (exponential in the dimensionality of the state) have been required. Another approach is to add new resources as needed, by adding new parameters or terms to the model structure. Such techniques are being explored in the field of neural networks where new neurons are added to an existing net, and in statistics where approaches such as additive regression and projection pursuit add new terms to the model. These techniques, although promising, have not been adequately evaluated in adaptive control applications.

3 Approach

3.1 Nonparametric Modeling Based On A Locally Weighted Criterion

We have chosen to explore a different approach that avoids difficult issues such as choosing an appropriate model structure in advance of collecting the data [4,7]. The locally weighted modeling approach simply stores data, which in a typical application would be the modeling errors of a parametric model based on knowledge of the plant. When a query is made to the parametric model, a new local correction model is formed using a locally weighted training criterion:

$$C_{\mathbf{q}}(\beta) = \sum_i \left[(f(\mathbf{x}_i, \beta) - y_i)^2 K(d(\mathbf{x}_i, \mathbf{q}))\right] \tag{1}$$

the ith training data point has an input vector $\mathbf{x}_i$ and an output y_i, $f()$ is a model structure with a parameter vector β, $K()$ is the weighting or kernel function such as a one dimensional Gaussian, and $d(\mathbf{x}_i, \mathbf{q})$ is the distance between the data point $\mathbf{x}_i$ and the query $\mathbf{q}$. Using this training criterion, $f(\mathbf{x}, \beta)$ becomes a *local* model, and can have a different set of parameters β for each query point $\mathbf{q}$ [7].

The locally weighted modeling approach has excellent asymptotic properties, but little is known about how well it will perform on finite data sets. We have applied it to the control of robots with excellent results [1,2,8].

Linear systems require persistent excitation for accurate system identification. With nonlinear systems and an approximately correct model structure, the parameters identified depend on the data distribution. Negative interference is the loss of the ability to fit a previous data distribution because of training on a new data distribution. Locally weighted modeling avoids negative interference by retaining the original training data, so the approach is adaptive to changing data distributions [7].

3.2 Nonlinear Controller Design Based On Dynamic Programming

Dynamic programming provides a methodology to design controllers and estimators for nonlinear systems. However, general dynamic programming is intractable. We explored using dynamic programming in tubes around the trajectory of a maneuver, and in bubbles around

a goal state. We used sophisticated representations of high dimensional sub-manifolds to enable dynamic programming in higher dimensional spaces than are currently possible [3,9,10].

4 Results

We developed several nonparametric modeling techniques [1,4,6,7] as well as controller design techniques [2,3,8,9,10] for high performance control of maneuvers. We explored these schemes in simulation as well as implementing them on a nonlinear testbed. The nonlinear testbed was a complex seven degree of freedom robot arm. These implementations worked well, demonstrated real-time learning, and avoided negative interference when learning different maneuvers. The techniques were capable of learning maneuvers both autonomously and from demonstrations by experts. These implementations demonstrated the potential of control design techniques based on learned local nonparametric models.

We developed and implemented techniques to improve the performance of locally weighted modeling in the areas of:

- Modeling the bias and variance of locally weighted model predictions. Our predictions are linear in the data, leading to straightforward estimates of prediction bias, variance, and confidence intervals.
- Globally optimizing fit parameters such as distance metrics, ridge regression parameters, outlier rejection thresholds, and weighting function parameters.
- Identifying and eliminating locally irrelevant terms in the model.
- Locally optimizing fit parameters such as a smoothing parameter or bandwidth.
- Faster implementations that also use less memory based on using "receptive fields", each of which maintains a local model.

4.1 Air Force Benefits

Success in this research can have several practical consequences. Learning systems can allow us to increase the performance range of a given vehicle. Learning systems can optimize performance, improving efficiency, range, and agility. Terrain may be followed more closely, and better pursuit and evasive maneuvers may be possible. Learning systems may also allow us to make use of less costly components in manned and unmanned vehicles, and allow the use of less expensive instrumentation and manufacturing processes to produce parts and vehicles with less exacting tolerances. Learning can correct for component inaccuracies as long as each component is individually repeatable. Learning systems may make complex manned and unmanned vehicles easier to fly, and easier to train pilots for. Specific pilot training modes can be developed. Learning systems may make unmanned vehicles usable for a wider range of missions and ground controller skills, and ground crew requirements for UAVs may be reduced. The research can lead to less expensive design processes for control systems.

5 Future Work

We have shown that our nonparametric modelling techniques are successful in modeling nonlinear systems. However, an open question is how to use these nonparametric nonlinear models to design robust control systems. We have derived the bias and variance for our local modeling approaches, and expressions for the uncertainty of local model parameters. These techniques can be used directly in robust controller design approaches, and in dynamic programming to choose how to explore optimally, in addition to controlling optimally.

6 Personnel Supported

Salary support was provided to the PI: Prof. Christopher G. Atkeson and to a graduate student, Gary Boone.

7 Publications

1. Schaal, S. and C. G. Atkeson, "Robot Learning By Nonparametric Regression" *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Munich, Germany, 1994.

2. Atkeson, C. G., and S. Schaal, "Memory-Based Neural Networks For Robot Learning", *Neurocomputing,* 9(3):243-69, 1995.

3. Moore, A. M., and C. G. Atkeson, "The Parti-game Algorithm for Variable Resolution Reinforcement Learning in Multidimensional State Spaces", *Machine Learning,* 21(3):199-233, 1995.

4. Schaal, S. and C. G. Atkeson, "From Isolation to Cooperation: An Alternative View of a System of Experts", *Proceedings, Neural Information Processing Systems,* Denver, Colorado, December, 1995, In: *Neural Information Processing Systems 8.* MIT Press, 1996.

5. Schaal, S., D. Sternad and C. G. Atkeson, "One-handed Juggling: Dynamical Approaches to a Rhythmic Movement Task" *Journal of Motor Behavior*, 28(2):165-183, 1996.

6. Zhao, Y., and C. G. Atkeson, "Implementing Projection Pursuit Learning", *Transactions on Neural Networks,* 7(2):362–73, 1996

7. Christopher G. Atkeson, Andrew W. Moore, Stefan Schaal, "Locally Weighted Learning", *Artificial Intelligence Review*, in press.

8. Atkeson, C. G., A. W. Moore, and S. Schaal, "Locally Weighted Learning for Control", *Artificial Intelligence Review*, in press.

9. Atkeson, C. G., "Learning From A Single Demonstration", *International Conference on Robotics and Automation*, 1997.

10. Atkeson, C. G. and J. C. Santamaria, "A Comparison of Direct and Model-Based Reinforcement Learning", *International Conference on Robotics and Automation*, 1997.

8 Interactions/Transitions

8.1 Presentations not covered in *Publications*

- Atkeson, C. G., "Perspectives On Robot Learning", 1994 American Association for Artificial Intelligence Conference, Seattle, Washington, August 2, 1994
- Atkeson, C. G., "Nonparametric Modeling and Control of High Performance Maneuvers", AFOSR Contractors/Grantees Meeting in Dynamics and Control, Minneapolis, Minnesota, June 5-7, 1995.

8.2 Consultative and Advisory Functions

Member, review panel, National Science Foundation program on Robotics and Machine Intelligence. Reviewed approximately 40 proposals. Met in Washington DC April 5. 1995. Program manager is Howard Moraff.

8.3 Transitions: Technology Transfer And Dual Use

None.

9 Inventions and Patents

None.

10 Honors/Awards

None.